Why does cue polarity information provide benefits in inference problems? The role of strategy selection and knowledge of cue importance

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Why does cue polarity information provide benefits in inference problems?

The role of strategy selection and knowledge of cue importance

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Abstract

Knowledge about cue polarity (i.e., the sign of a cue-criterion relation) seems to boost performance in a wide range of inference tasks. Knowledge about cue polarity information may enhance performance by increasing (1) the reliance on rule- relative to similarity-based strategies, and (2) explicit knowledge about the relative importance of cues. We investigated the relative contribution of these two mechanisms in a multiple-cue judgment task and a categorization task, which typically differ in the inference strategies they elicit and potentially the explicit task knowledge available to participants. In both tasks participants preferred rule-based relative to similarity-based strategies and had more knowledge about cue importance when cue polarity information was provided. Strategy selection was not related to increases in performance in the categorization task and could only partly explain increases in performance in the judgment task. In contrast, explicit knowledge about the importance of cues was related to better performance in both categorization and judgment independently of the strategy used. In sum, our results suggest that the benefits of receiving cue polarity information may span across tasks, such multiple-cue judgment and categorization, primarily by enhancing knowledge of relative cue importance.

Keywords: category learning; judgment; decision making; knowledge; computational modeling

1. Introduction

Professionals such as teachers, doctors, and lawyers are specifically trained to make decisions about grades, procedures, and sentences that have profound effects on people's lives. But how should decision-making be taught and which information should be given to such professionals to ensure good decisions? Our work makes a small contribution to this issue by investigating how providing a specific type of information to individuals affects performance in different tasks. Research suggests that providing task information to decision makers has a positive impact on performance (e.g., Balzer et al., 1989; Murphy, 2002). However, why knowledge increases performance and the degree to which performance increases are specific to particular tasks or inference strategies is less well understood. The goal of this paper is to investigate the mechanisms by which providing one type of knowledge, namely, cue polarity information (i.e., the sign of a cue-criterion relation) influences individuals' performance in judgment and categorization tasks.

1.1. The effects of prior information: Cue polarity

Tasks that are embedded in meaningful contexts usually yield better performance than context-free tasks (Adelman, 1981; Evans et al., 2005; Kaplan and Murphy, 2000; Muchinsky and Dudycha, 1975; for reviews see Heit, 1997 or Murphy, 2002). For example, Muchinsky and Dudycha (1975) showed that participants predicted applicants' "credit scores" significantly better based on "debt" and "number of creditors" than when the same information was provided as "criterion", "cue 1", and "cue 2". Overall, giving task information has been shown to increase performance in judgment tasks (e.g., Balzer et al., 1989; Balzer et al., 1992). One piece of information that seems to be especially helpful and which could explain the beneficial effect of context information is *cue polarity*. According to Dawes and Corrigan (1974), knowing cue polarity is a crucial factor for successful performance in judgment. In line with this view, a few findings suggest that providing cue polarity information—that is, providing initial knowledge about the sign of cue-criterion relations (positive vs. negative)—improves performance in inference tasks such as categorization (Newell et al., 2009), and multiple-cue judgment (von Helversen and Rieskamp, 2009). In this paper we will investigate two mechanisms that could underlie performance increases: (1) strategy selection and (2) explicit knowledge about cue importance.

1.2. Cognitive strategies in categorization and judgment

Psychological theories of categorization and judgment suggest that people use at least two broad types of strategies to solve inference problems: rule-based strategies (e.g., Bruner et al., 1956; Einhorn et al., 1979) and similarity-based strategies (e.g., Medin and Schaffer, 1978; Nosofsky and Johansen, 2000). A prototypical rule-based strategy that is frequently used in inferences tasks is the cue abstraction strategy. The cue abstraction strategy assumes that a judgment or decision rule is identified by abstracting the relation of individual pieces of information (i.e., *cues*) to the *criterion*. For example, a doctor may prescribe a specific treatment (criterion) based on a few critical symptoms (cues) such as fever duration or magnitude, weighted by their respective importance. The cue abstraction strategy can be described by a linear additive model such as multiple linear regression (e.g. Brehmer, 1994; Cooksey, 1996; Juslin et al., 2003).

In turn, an inference is considered similarity-based if it relies on the similarity of a probe to exemplars retrieved from memory (e.g., Medin and Schaffer, 1978), such as when a doctor prescribes a treatment based on the patient's symptom-profile being similar to a previously encountered patient, where the similarity is determined by the overlap of the patients' symptoms weighted by the attention allocated to them. Similarity-based judgments are frequently described by exemplar models (Juslin et al., 2008; Nosofosky and Johansen, 2000; Hoffmann et al., 2013).

Both rule-based and similarity-based strategies have been observed in categorization (e.g., Allen and Brooks, 1991; Ashby et al., 1998; Pachur and Olsson, 2012), judgment (e.g., Juslin et al., 2008; von Helversen and Rieskamp, 2008), decision-making (e.g., Juslin and Persson, 2002; Pachur and Olsson, 2012), and induction tasks (e.g., Sloutsky et al., 2007). Past research suggests, however, that a preference for rule- over similarity-based processes is usually the norm, that is, individuals try to learn cue–criterion relations to use in a rule-based fashion and only default to exemplar-based strategies as a backup solution (Juslin et al., 2003; Nosofsky and Bergert, 2007; Platzer and Bröder, 2012). The frequency with which different strategies are selected depends on the nature of the task representation, which in turn may depend on the characteristics of the task. There is consensus that some task structures may facilitate the abstraction of cue-criterion relations and thus the use of rule- versus similarity-based strategies (Juslin et al., 2008). For instance, a rule-based cue abstraction strategy is chosen more frequently in linear judgment tasks (i.e. the criterion is a linear function of the cues), whereas similarity-based exemplar strategies are preferred in non-linear judgment tasks (i.e. the criterion is a nonlinear function of the cues, Hoffmann et al., 2013; Juslin et al., 2008; Pachur and Olsson, 2012). The rationale being that linear relations can be learned and represented by an explicit model of cue abstraction, while non-linear cue-criterion relations cannot, and thus the task must be solved by a similarity-based strategy.

Providing cue polarity information may similarly foster the use of rule-based strategies by enabling the accurate and explicit representation of cue-criterion relations. Indeed, evidence is mounting that receiving cue polarity information increases the reliance on rule-based over similarity-based strategies. For instance, Platzer and Bröder (2012) found that providing cue polarity information induced a shift to rule-based processing in a memory-based paired comparison task (see also Bröder et al., 2010). Similarly, von Helversen and

Rieskamp (2009) reported a stronger reliance on a rule- relative to a similarity-based strategy in a non-linear multiple-cue judgment task when cue polarity information was available. But what are the consequences of such changes in strategy selection and task representation on performance?

1.3. Strategy selection and performance

In linear tasks, reliance on rule-based processing may lead to superior performance because a cue abstraction strategy matches the underlying task-structure. This not only enables accurate performance in a training sample but also allows judges to accurately generalize to new cases, even if they require extrapolation that is judgments outside the range of experienced criterion values. In contrast, similarity-based processing may not capture the task-structure in linear tasks when provided with limited training (Juslin et al., 2003). Thus, even if users of an exemplar strategy perform well in a training sample, the good performance may not generalize to new cases. In particular, exemplar-based strategies fail at extrapolation, because they cannot predict a value outside of the previously experienced range of values (see also Delosh et al., 1997; Pachur and Olsson, 2012). In this vein, research shows an advantage for rule-based strategies over similarity-based strategies in a variety of linear tasks such as judgment (Hoffmann et al., 2013; von Helversen et al., 2010) and paired comparison (Pachur and Olsson, 2012). Furthermore, Newell and colleagues (2009) found that when cue polarity information was provided in a probabilistic categorization task, participants not only performed better, but their responses were also well described by a rule-based strategy.

Note that the performance advantages of relying on a cue abstraction strategy relative to an exemplar-based strategy should apply to both categorization and multiple-cue judgment under limited training conditions (cf. von Helversen et al., 2010; Juslin et al., 2008). However, in practice the relative advantage of human judges relying on cue abstraction differs between judgment and categorization tasks: Empirical results suggest that cue abstraction users perform better than exemplar users in (linear) judgment tasks, but show similar or inferior performance relative to exemplar users in (linear) categorization tasks (Hoffmann et al., 2013; Mata et al., 2012; von Helversen et al., 2010; von Helversen and Rieskamp, 2008). One reason why performance differences between exemplar and cue abstraction strategies are observed in judgment but not in categorization tasks could be the differential ease with which the information necessary for a cue abstraction strategy is learnt in judgment versus categorization. When solving a judgment task, people receive more fine-grained feedback about the criterion than when solving a categorization task. The more fine-grained feedback likely facilitates learning cue polarities and relative cue importance (see the next section) necessary for applying a cue abstraction strategy. This is the case because objects that differ in their cue values may fall into the same category in a categorization task, but still have different criterion values in a judgment task. This difference in criterion values, in turn, can be used to infer cue polarity. Accordingly, people may find it more difficult to learn cue polarities in categorization, which in turn could lead to a suboptimal execution of the strategy or even a switch to exemplar-based strategies. Indeed, Platzer and Bröder (2012) found that the quality of cue abstraction knowledge mediated the shift to rule-based strategies in a paired comparison task. In addition, often more people are classified as users of an exemplar-based strategy relative to users of a cue abstraction strategy in categorization than in judgment tasks (Juslin et al., 2003; Mata et al., 2012; von Helversen et al., 2010, but see Pachur and Olsson, 2012[1]).

In light of the reasons listed above, providing cue polarity information will likely increase reliance on cue abstraction, which will in turn benefit performance in (linear) judgment tasks. The impact of providing cue polarity information and the possible shift to cue

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[1] Contrary to other findings in the literature, Pachur and Olsson (2012) did not find a larger number of exemplar strategy users in a categorization relative to a judgment task. One potential reason for the diverging results may be that Pachur and Olsson provided participants with feedback about the continuous criterion value in both, the categorization and judgment tasks.

abstraction in categorization is less clear. If cue abstraction users are unable to outperform exemplar-based ones because they fail to learn cue polarity information, explicitly instructing participants about cue polarities may lead to increased reliance on cue abstraction and, ultimately, improve performance. Alternatively, to the extent that providing cue polarity information is not enough to produce a significant improvement on the execution of a cue abstraction strategy, it is possible that providing judges with cue polarity information does not lead to performance benefits. One factor that may be crucial to increasing performance is the extent to which providing cue polarity information also contributes to improving knowledge of relative cue importance—an issue we turn to next.

1.4. Knowledge of cue importance and performance

A second mechanism underlying how cue polarity information can improve performance is by increasing the knowledge participants have about the importance of the cues. Good performance in a multiple cue judgment task requires—besides knowledge about the cue polarity—knowledge about the relative importance of the cues' performance (Brehmer, 1979, 1994). Eliminating the need to learn cue polarity information may liberate resources necessary to learn the relative cue importance (i.e., cue weights) used by cue abstraction strategies. Indeed, Platzer and Bröder (2012) found that participants had better knowledge about the cue validities when cue polarity information was provided. Better knowledge of cue importance, in turn, should enhance performance by improving how well a strategy is executed.

It is unclear, however, if knowledge about cue importance will benefit users of cue abstraction and exemplar-based strategies equally. Platzer and Bröder (2012) found that better explicit knowledge predicted choosing a rule-based strategy. This suggests that users of an exemplar-based strategy do not acquire explicit knowledge about the task, resonating with the idea that using a similarity-based strategy is a largely implicit process (Ashby et al., 1998).

Accordingly, this would suggest that explicit knowledge is associated with performance for cue abstraction users but not for exemplar users. Notwithstanding, knowledge about cue importance could improve performance independently of the strategy selected. Rehder and Hoffman (2005) found the amount of attention given to relevant cues was positively associated with performance when using a similarity-based strategy. Thus, knowledge about cue importance may improve performance by guiding the amount of attention given to specific cues when using a similarity-based strategy.

In sum, there are two potential mechanisms that could explain why cue polarity information increases performance in inference tasks, namely by increasing (1) the reliance of rule-based over exemplar-based strategies in the appropriate environment and (2) the knowledge of relative cue importance necessary for guiding attention or weighting of cues. We conducted two studies to find out how these two mechanisms affect performance. In study 1, we concentrated on how cue polarity information impacts strategy selection and whether it influences performance similarly in categorization and judgment tasks. In study 2, we went one step further and examined how cue polarity knowledge is related to explicit knowledge about cue importance, and its links to strategy selection and performance.

2. Study 1

The goal of study 1 was to investigate whether cue polarity information increases reliance on rule-based relative to similarity-based strategies and if this shift is related to performance increases in both judgment and categorization.

2.1. Method

2.1.1. Participants

Ninety-four young adults participated in the task (M_{age} = 25.9 years, *SD* = 3.44; 50% females). Most participants were students of one of the Berlin universities, on average in their

5th year of studies. The study lasted for approximately 1.5h. Participants were paid performance dependent and earned on average €11.1 (plus a €5 show-up fee).

2.1.2. Design and procedure

The participants' task was to judge how successful cartoon characters, the Sonics, were in a hunting game (see Juslin et al., 2003; Mata et al., 2012, for similar designs; details on the instructions can be found in the supplementary material A). Participants could use four binary cues to make the judgments (i.e., type of ears, type of nose, color of the belly, and hairstyle, which were pretested to ensure equal salience, see von Helversen et al., 2010). We varied the type of task (categorization vs. judgment; between-subjects) and whether participants received information about the polarity of the cues prior to the task (information vs. no information; between-subjects). In the categorization task participants had to decide whether a Sonic was a successful or an unsuccessful player. In the multiple-cue judgment task participants had to give an estimate of how many points a Sonic would win in the game on a scale from 10 to 20. In the no-information condition participants were told that they would have the opportunity to learn which Sonics were successful during a training phase. In the information condition participants received additional cue polarity information; that is, they were shown which cue values would indicate a successful player. The training phase consisted of 10 Sonics that were shown block wise (see Table 1).

After the training phase, a test phase followed during which participants judged all possible 16 Sonics four times (i.e., 10 old items from the training phase and 6 new transfer items that they had not seen before). The 10 Sonics used in the training set were selected so that relying on an exemplar and a cue abstraction strategy would result in different judgments for the new objects in the test phase given the assumption that the two strategies were applied without error. In each block of the training phase the 10 Sonics were presented in a random order. In each training trial participants saw a Sonic and were asked to judge it. Afterwards they received feedback and continued with the next Sonic. The training phase continued for a minimum of 8 blocks and a maximum of 16 blocks. After the initial 8 blocks, training stopped if participants passed an accuracy criterion. We used an accuracy criterion for several reasons. For one, an accuracy criterion allows focusing on participants that took the task seriously and managed to solve it reasonably well. Additionally, a learning criterion allows better comparison between individuals because it minimizes differences in performance at the end of training. The accuracy criterion was set at 0.5 root mean square deviation (*RMSD*) for the categorization task (equivalent to correctly classifying 8 out of 10 exemplars) and at 1.5 *RMSD* for the judgment task. Participants were paid according to their performance in the task. In the categorization task, participants received 10 points for every correct classification. In the judgment task, participants received 10 points if they judged the correct criterion value, 5 points if they deviated by only one point, and zero points otherwise. After the task, points were exchanged into Euros at a rate of €1 for 100 points and paid to the participants.

2.1.3. Materials

The Sonics could have one of two cue values on each cue (i.e., spiky hair vs. dreadlocks), which were randomly assigned a zero or one. In the multiple-cue judgment task the criterion C was a linear additive function of the cue values.

$$C = 10 + 4c_1 + 3c_2 + 2\,c_3 + 1c_4 \qquad (1)$$

The criterion in the categorization task was constructed from the criterion in the judgment task: Sonics making more than 15 points were classified as successful and Sonics making less than 15 points as unsuccessful. Details on the task structure can be found in Table 1.

2.2. Results

In the following, we first report how cue polarity information affected participants' performance in the categorization and judgment tasks. We then assess the impact of providing cue polarity information on the reliance on rule-based vs. similarity-based processes. We analyzed the results for the categorization and the judgment task separately because the performance measures are not on the same scale and thus do not allow a direct comparison between the categorization and judgment tasks.

2.2.1. Performance

As measures of performance we considered learning speed (measured by the number of blocks participants needed to reach the learning criterion), learning performance (measured by the accuracy at the end of the learning phase), and test performance (measured by the accuracy in the test phase; see Table 2 for means and SDs). We measured accuracy as the *RMSD* between participants' judgments (averaged across the four repetitions in the test phase) and the criterion. In the test phase we separately considered accuracy for old items (i.e., items known from the training phase) and transfer items (i.e., new items that participants had not seen before). We consider performance for old and new items separately, because performance differences are particularly likely on the new items. While both strategies can in principle perfectly learn to judge the training set, the degree to which the two strategies allow correctly generalizing to the new items differs; whereas the cue abstraction model matches the structure of the task, the exemplar model does not, leading to a higher expected performance of the cue abstraction model on the new, but not on the old items (see also Table 1).

We compared performance with and without cue polarity information in the judgment and the categorization task separately using *t*-tests. If the variances in the two groups differed we adjusted the degrees of freedom according to the Welch correction. In the judgment task, participants needed fewer blocks when cue polarity information was given than when no cue polarity information was given, $t(30.25) = 3.99$ $p < .001$. Participants with cue polarity information also performed better at the end of the training phase than participants without cue polarity information, $t(48) = 3.37$, $p = .002$, even though they received less training. Similarly, participants with cue polarity information performed better in the test phase than participants without cue polarity information, for the old items, $t(48) = 2.89$, $p = .01$, as well as for the transfer items, $t(48) = 4.40$, $p < .001$. Because we had found differences in performance at the end of training, we conducted analyses of variance for the performance measures in the test phase, adding performance at the end of training as a covariate. The goal of these analyses was to exclude that better results at test were only due to differences in learning. These analyses showed that the effect of cue polarity information was not longer significant for the old items, but the effect of cue polarity information on the new items remained significant.

In the categorization task, participants with cue polarity information needed somewhat fewer blocks than participants without cue polarity information, $t(27.08) = 1.98$, $p = .06$, but they did not perform better at the end of training, $t(42) = 0.95$, $p = .35$, or during the test phase, for neither old items, $t(42) = 1.50$, $p = .14$, nor new items, $t(42) = 0.1$, $p = .99$. In sum, cue polarity improved performance in the judgment task, but not in the categorization task.

2.2.2. Model classification

To determine if participants relied on a cue abstraction or an exemplar-based strategy, we relied on a computational modeling approach. We modeled participants' responses with an exemplar model and a cue abstraction model and then classified them to the better fitting strategy.

2.2.2.1 Exemplar model

The exemplar model assumes that the estimated criterion value $\hat{y}_p$ for the probe *p* is the average of the criterion values *c*, weighted by their similarity to the probe,

$$\hat{y}_p = \frac{\sum_{i=1}^{I} S(p,i) \cdot x_i}{\sum_{i=1}^{I} S(p,i)}, \tag{2}$$

where *S* is the similarity of the probe to the stored exemplars; x_i is the criterion value of the exemplar *i*; and *I* is the number of stored exemplars in memory. In the judgment task we used the number of Golbis caught as the criterion and in the categorization task the probability of a Sonic being classified as successful. The similarity between the stored exemplar and the probe is calculated by the similarity rule of the *generalized context model* (GCM, Nosofsky, 1984):

Specifically, the similarity between exemplars is found by transforming the distance between them. The distance *d* between a probe *p* and an exemplar *i* is

$$d_{pi} = h\left[\sum_{j=1}^{J} s_j \left|c_{pj} - c_{ij}\right|\right], \tag{3}$$

where c_{pj} and c_{ij}, respectively, are the cue values of the probe *p* and an exemplar *i* on cue dimension *j, h* is a sensitivity parameter that reflects discriminability in psychological space (Nosofsky and Zaki, 1998) and the parameters s_j are the attention weights associated with cue dimension *j*. Attention weights vary between 0 and 1 and are constrained to sum to 1. The similarity *S* between a probe *p* and an exemplar *i* is a nonlinearly decreasing function of their distance (d_{pi})

$$S(p,i) = e^{-d_{pi}}. \tag{4}$$

2.2.2.2 Cue abstraction

The cue abstraction model assumes that the judgment $\hat{y}$ of an object p is the sum of the weighted cue values $c_1 \ldots c_j$, plus an intercept k.

$$\hat{y}_p = k + \sum_{1=j}^{J} w_j \cdot c_j, \tag{5}$$

where the intercept k and the weights w are free parameters. If $k = 10$. $w_1 = 4$. $w_2 = 3$. $w_3 = 2$ and $w_4 = 1$, equation 5 is identical to the function determining the continuous criterion and the model produces perfect judgments.

In the binary task, we modeled the proportion of Sonics classified as successful $p(b=1)$ by a smoother logistic function to take into account random error (c.f. Juslin et al., 2003):

$$\hat{p}\left(\hat{b} = 1\right) = \frac{e^{k+\sum W_i \cdot c_i}}{1 - e^{k+\sum W_i \cdot c_i}}. \tag{6}$$

where W_i are the cue weights and k the intercept.

2.2.2.3 Model fitting and classification

To determine which model best described participants' responses we relied on a leave-one-out cross-validation method (cf. von Helversen et al., 2010). We fitted each models' free parameters on the average response of an individual participant to fifteen of the test items, minimizing the sum of squares between the participants' responses and the models' predictions. We then predicted with the estimated parameter values the response to the sixteenth item. This was repeated for all sixteen test items. The final goodness-of-fit measure was the *RMSD* between the model predictions on the sixteen predicted items and participants' responses. For the exemplar model, we fitted four free parameters, an attention weight for each cue constrained to sum to one and a sensitivity parameter, with a nonlinear least square algorithm (*lsqcurvefit* function from the optimization toolbox in Matlab). To fit the cue abstraction model we run a multiple linear regression on the individual judgments. In the categorization task, we fitted a logistic regression and then optimized parameters with a nonlinear least square fit (see exemplar model), constraining the intercept to fall between -10 and 10 to receive more stable estimates. Model fits are reported in the supplementary material B, mean model fits in Table S1 and individual model fits in Table S2.

We classified participants according to the model that fit their responses best (see Table S2). To ensure a robust classification we only classified participants for which the difference in fits by the two models was larger than one standard error of the overall model fits in this condition. In the judgment task, 5 participants without information, and 3 with information could not be unambiguously classified. In the categorization task, 7 participants in the condition without information could not be classified. We excluded these participants from further analyses that relied on participant classification. We then tested if providing cue polarity information induced participants to rely on a cue abstraction strategy. As illustrated in Figure 1, the majority of participants in the judgment task was classified as using cue abstraction regardless of whether cue polarity information was provided (see Table 3); nevertheless, Chi-square tests indicated that if cue polarity information was given, the number of cue abstraction users somewhat increased, $X^2(1,42) = 4.18$, $p = .06$. More dramatically, in the categorization task without cue polarity information, the majority of participants was classified as exemplar users, whereas in the condition with prior information the majority was classified as cue abstraction users, $X^2(1,37) = 14.60$, $p < .001$.

In sum, without cue polarity information there was a stronger reliance on a similarity-based exemplar- strategy in the categorization than in the multiple-cue judgment task. However, receiving cue polarity information led to almost exclusive reliance on rule-based cue abstraction strategy in both categorization and judgment tasks.

2.2.3. Model classification and performance

Next, we tested whether strategy selection was related to performance. We focused on the new items, because differences between strategies are more likely to be reflected on the new items, however the pattern of results is similar when using the complete test set. Zero-order correlations indicated a significant correlation between strategy selection and performance on the new test items in the judgment, $r(42) = .36$, $p = .02$, but not in the categorization task, $r(37) = .07$, $p = .66$. We tested whether cue polarity information provided an influence on performance above the influence of strategy selection by conducting a follow-up regression analysis: The analysis showed that in the judgment task cue polarity information was still a significant predictor of performance on the new test items, when strategy selection was included as an additional predictor, $b = -.48$, $t(39) = 3.54$, $p = .001$. In the categorization task, neither cue polarity information nor strategy selection influenced performance (ps > .80).

2.3. Discussion study 1

Study 1 examined whether providing cue polarity information increases performance through its impact on strategy selection. Consistent with prior research, we found that when cue polarity information was provided participants in both judgment and categorization tasks preferred a cue abstraction strategy relative to an exemplar-based strategy (Platzer and Bröder, 2012; Bröder et al., 2010; von Helversen and Rieskamp, 2009). However, whereas in the categorization task the dominant strategy changed, in the judgment task the increase in cue abstraction users was less pronounced. This was mainly due to a larger number of cue abstraction users in the judgment than in the categorization task when no cue polarity information was provided. These results resonate with prior research reporting more users of an exemplar-based strategy than users of cue abstraction in categorization (Juslin et al., 2003; Mata et al., 2012). They also are consistent with the hypothesis that people rely on exemplar-based strategies in categorization tasks without cue polarity information because strategy selection depends on the ease with which cue polarities can be abstracted (for a similar argument see, Platzer and Bröder, 2012; Pachur and Olsson, 2012).

Concerning potential performance benefits of providing cue polarity information, we found that participants in the categorization task did not perform better when cue polarity information was provided. This suggests that although people may switch to a cue abstraction strategy when cue polarity information is available, the differences in accuracy between the exemplar-based and cue abstraction strategies are not enough to cause a significant increase in performance. One reason why performance between users of an exemplar-based and a cue abstraction strategy did not differ in categorization is that they were masked by reliance on a less sensitive performance measure in categorization than in judgment. However, additional analyses using a binary performance measure in both tasks, showed the same pattern of results. [2] Another reason could be, that in categorization cue abstraction users do not manage to execute the cue abstraction strategy well enough to reach a noticeable differences in performance to an exemplar-based strategy, resulting in a similar performance of both strategies.

In contrast, in the judgment task, cue polarity information was related to better performance, providing further evidence that cue polarity information improves inferences (e.g., Newell et al., 2009). Furthermore, selecting a cue abstraction strategy was positively related to performance as would be expected in a linear judgment task (e.g. Hoffmann et al., 2013). The influence of cue polarity information on performance, however, remained significant, even if strategy selection was included as a predictor. This suggests that the

[2] We examined the sensitivity issue by conducting analyses for both, multiple-cue judgment and categorization, using a binary performance measure. For this measure we classified judgments > 15 as a "successful" response, judgments < 15 as a "not successful" response, and judgments = 15 as having a probability of 0.5 of being a "successful" or "not successful" response. We then calculated the percentage of correct responses in both tasks. The results based on this performance measure are similar in that they suggest (1) a superior performance of cue abstraction relative to exemplar-based users in the multiple-cue judgment but not the categorization task and (2) a superior performance with cue polarity information in the multiple cue judgment but not in the categorization task.

performance benefits of cue polarity information in the judgment task may not be solely attributable to a switch in strategy selection.

In sum, study 1 showed that cue polarity information increased performance in judgment, but not in categorization, and found some support that strategy selection is linked to performance in the judgment task. Interestingly, strategy selection could not explain all variance in performance, suggesting that further mechanisms play a role. In study 2 we considered knowledge about cue importance as a further mechanism underlying how cue polarity information may increase performance.

3. Study 2

Study 2 investigated whether providing cue polarity information increased explicit knowledge about relative cue importance and how knowledge about cue importance and strategy selection contributed to performance. In addition we increased the sample size and the learning criterion to ensure that the lack of performance increase in categorization was not due to insufficient learning.

3.1. Method

3.1.1. Participants

In study 2, 155 students (41% female) from Clarkson University participated for course credit and a performance-dependent incentive. Participants were randomly assigned to the four conditions with 39 participants in the categorization condition with information, 41 participants in the categorization condition without information, 37 participants in the judgment condition with information, and 38 participants in the judgment condition without information. Participants were on average 19.6 years old (*SD* = 1.36).

3.1.2. Design and materials

Study 2 was a replication of study 1 with some minor changes. In particular, we increased the number of training trials and the learning criterion to achieve better mastering of training items. The training phase continued until a maximum of 200 learning trials had been completed or until a *RMSD* of 1 had been reached in the judgment task. In the categorization task, the training criterion was reached if in two consecutive blocks only one Sonic was falsely classified, corresponding to a *RMSD* of 0.2. We also changed the payoff structure to incentivize speedy learning. In study 2, participants entered a lottery for $100 in each condition. During the study they could earn points that were translated into lottery tickets at the end of the experiment. In the training phase participants could earn 500 points if they reached the training criterion. Participants continued with the test phase as soon as the learning criterion had been reached. In the test phase, participants could earn additional points with their judgments, according to the same payoff scheme as in study 1. For details on instructions see supplementary material A. At the end of study 2 we asked participants about their knowledge about cue polarity and cue importance. To measure their knowledge about cue polarity we asked them to indicate the direction of each cue (positive, negative). In addition, participants indicated the relative importance of each cue by distributing 100 points across the four cues as a function of their importance.

3.2. Results

3.2.1 Performance

As in study 1, we analyzed if cue polarity information increased performance separately in the categorization and the judgment task. First, we examined how many participants reached the learning criterion. The analysis showed that in both tasks more participants reached the learning criterion when cue polarity information was given. In the categorization task, 11 of 41 did not reach the learning criterion when no information was given, but only 2 of 39 failed to reach the criterion when cue polarity information was available, $X^2(1,80) = 6.92$, $p = .01$. In the judgment task, 26 of 38 did not reach the criterion when no information was given, but only 6 of 37 failed to do so when cue polarity information was available, $X^2(1,75) = 20.89$, $p < .001$. In the following analyses, we included all participants but the conclusions do not change when only including the participants that reached the learning criterion.

We measured performance as learning speed, learning performance (accuracy at the end of the learning phase), and test performance (accuracy during test; see Table 4) and tested for an effect of cue polarity using *t*-tests. If the variance between groups differed, we adjusted the degrees of freedom according to the Welch correction. As in the first study, we analyzed performance for old and new items separately because performance differences due to strategy selection should be more marked in the new items. In the judgment task, participants with cue polarity information required fewer learning blocks, $t(73) = 6.30$, $p < .001$, performed better at the end of training, $t(73) = 3.29$, $p = .002$, and performed better at test, old items, $t(73) = 4.73$, $p < .001$, new items, $t(73) = 5.84$, $p < .001$. Providing cue polarity information also improved performance in the categorization task. Participants with cue polarity information required fewer training blocks, $t(78) = 4.52$, $p < .001$, performed better at the end of training, $t(51.92) = 2.92$, $p = .005$, and performed better at test, old items, $t(73.02) = 1.73$, $p = .09$, new items, $t(78) = 3.17$, $p = .002$. Because we had found differences in performance at the end of training, we conducted analyses of variance for the performance measures in the test phase, adding performance at the end of training as a covariate. The goal of these analyses was to exclude that better results at test were only due to differences in learning. In both judgment and categorization, cue polarity still affected accuracy for the new test items, *p*s < .001. In the judgment task, cue polarity information also influenced performance on the old test items, $p = .002$, but not in the categorization task, $p = .26$. These results suggest that providing cue polarity information has an impact on performance on new items at test that goes beyond those of improved learning in the training phase.

3.2.2. Model classification

As in study 1, we fitted an exemplar model and a cue abstraction model to participants' responses and classified participants as users of their best-fitting model. Mean as well as individual model fits and classifications are reported in the supplementary material C in Tables S3 and S4, respectively. Five participants in the categorization condition could not be unambiguously classified to one of the models and were excluded from further analyses. Figure 2 presents the categorization results as a function of condition and task. In contrast to study 1, in the condition without information, we found similar percentages of exemplar strategy users in both the judgment and the categorization tasks. We used Chi-Square tests to analyze if cue polarity information influenced strategy selection. As expected, we replicated the finding in study 1 that providing information about cue polarity increased the percentage of cue abstraction users in the judgment, $X^2(1,70) = 21.05$ $p < .001$, and the categorization tasks, $X^2(1,74) = 13.93$, $p < .001$, see Table 5.

3.2.3. Knowledge about cue importance

To assess the quality of participants' knowledge about cue importance we created an index of cue importance knowledge. We calculated the index as a sum score of the absolute value (abs) of the difference between the cue importance indicated by a participant and the optimal cue importance for each cue (i.e., the cue weights in Equation 1 for each cue transferred to a scale from 0 to 100). Thus, a participant using the optimal weights would have a score of zero, whereas for example a participant considering only the first cue (i.e., giving it a weight of 100) but ignoring the other cues would have a score of 120 [i.e., abs(100-40) + abs(0-30) + abs(0-20) + abs(0-10)].

We then tested whether cue polarity information influenced the quality of cue importance knowledge in judgment and categorization (for means and *SD* see Table 4). Providing cue polarity information improved knowledge about cue importance both in the judgment, $t(73) = 2.79$, $p = .007$, and categorization tasks, $t(78) = 2.74$, $p = .008$. In a second step we investigated if the increase in knowledge depends on the selected strategy by running an analysis of variance (ANOVA) with cue importance knowledge as dependent variable and cue polarity information and model classification (exemplar-based/cue abstraction model) as between subject factors. In the judgment task, we found that participants classified as users of a cue abstraction strategy had better knowledge about cue importance than users of an exemplar-based strategy, $M_{EBM} = 50.71$, $SD = 26.26$ vs. $M_{CAM} = 25.48$, $SD = 24.72$, $F(1,66) = 9.41$, $p = .004$, but found no main effect of cue polarity information, $F(1,66) = 0.29$, $p = .59$, nor an interaction, $F(1,66) = 0.99$, $p = .32$. In the categorization task, we found no main effect of model or cue polarity information, but a significant interaction between the two factors, $F(1,70) = 5.38$, $p = .02$, suggesting that knowledge about cue importance increased for cue abstraction users with cue polarity information ($M_{\text{no info}} = 63$, $SD = 23.98$ vs. $M_{\text{info}} = 41.93$, $SD = 13.62$), but not for users of an exemplar-based strategy ($M_{\text{no info}} = 55.84$, $SD = 22.46$ vs. $M_{\text{info}} = 59.56$, $SD = 27.67$).

3.2.4. Model classification, cue importance knowledge, and performance

In a next step, we investigated how strategy selection and cue importance knowledge contributed to performance in judgment and categorization using hierarchical regression. We focused again on performance on the new items because they are more informative regarding strategy selection, however, analyses on the complete test set yield comparable results. In a first step, we regressed accuracy on the new test items on cue polarity information. In a second step, we included strategy classification and cue importance knowledge as additional predictors in the regression. In the judgment task, cue polarity information had a strong influence on performance in the first step. Further, strategy classification and cue importance knowledge both emerged as significant predictors but did not eliminate the effect of receiving cue polarity information (see Table 6). In the categorization task, cue polarity information also influenced performance in the first regression model. In the second step, however, only cue importance knowledge but neither strategy selection nor cue polarity information were significant predictors (see Table 6). Additionally, we conducted analyses that considered the interactions between strategy selection, knowledge of cue importance, and cue polarity information. However, because none of the interactions reached significance and otherwise the conclusions were unaffected we report here only the analyses without interactions.

3.3. Discussion Study 2

Consistent with study 1 we found that cue polarity information had an effect on participants' strategy selection, with a shift to rule-based processing when initially given cue polarity information (e.g., Platzer and Bröder, 2012). In contrast to study 1, we found that an exemplar model best described the majority of participants when no cue polarity information was provided in judgment and categorization. One possibility is that the strict learning criterion used in study 2 led participants to default to an exemplar-based strategy even in the judgment task that is typically associated with reliance on cue abstraction (Juslin et al., 2003; von Helversen et al., 2010).

Cue polarity information increased participants' knowledge about cue importance in both tasks, supporting the idea that providing cue polarity information facilitates the learning of the correct cue weights. Further analyses suggested that the observed increase in cue importance knowledge when cue polarity information was provided was related to the increase in cue abstraction users. In the judgment task, cue abstraction users had better knowledge about cue importance than exemplar users independently of cue polarity information. In the categorization task, knowledge about cue importance increased with cue polarity information for users of a cue abstraction strategy, but not for users of an exemplar-based strategy. This suggests that strategy selection and knowledge about cue importance may be closely linked, resonating with the work by Platzer and Bröder (2012) who showed that cue polarity information increases reliance on a cue abstraction strategy by improving knowledge about the task.

Analyses investigating the relative contribution of knowledge about cue importance and strategy selection suggested that a shift towards relying on cue-abstraction processes was related to superior performance in the judgment but not the categorization task. However, explicit knowledge about relative cue importance had a positive influence on performance in both the judgment and the categorization tasks. We discuss possible reasons for this last finding below.

4. General discussion

Common sense, as well as a wealth of experimental evidence, suggests that the more knowledge we have about a task the better we will perform at it (e.g., Balzer et al., 1989; Balzer et al., 1992; Heit et al., 2004; Hoffman et al., 2008; Kareleia and Hogarth, 2008). The goal of the present research was to investigate the benefits of providing judges with cue polarity information so as to tease apart its effects on both strategy selection and explicit task knowledge. To this end, we conducted two studies investigating whether providing cue polarity information increased knowledge about cue importance and reliance on a rule-based, cue abstraction strategy relative to a similarity-based, exemplar strategy in a categorization and a multiple-cue judgment task.

Providing participants with cue polarity information before the judgment and categorization tasks strongly affected participants' strategy selection. Specifically, participants relied more frequently on a cue abstraction strategy than an exemplar-based strategy after receiving cue polarity information. This shift was most impressive in a categorization task that typically involves the use of exemplar-based strategies (Juslin et al., 2003; von Helversen et al., 2010). These findings match recent results suggesting that prior knowledge about cue polarity can influence whether participants rely on a rule-based or a similarity-based strategy when making point estimates (von Helversen and Rieskamp, 2009), decisions (Bröder et al., 2010; Platzer and Bröder, 2012), or probabilistic categorizations (Newell et al., 2009).

Regarding performance, our results suggest that the effects of strategy selection on performance may be restricted to a linear multiple-cue judgment task. In study 1, we found benefits of cue polarity information in the judgment but not in the categorization task. In study 2, we found benefits of cue polarity information on both multiple-cue judgment and categorization but strategy selection was only predictive of increased performance in the judgment task. The results suggest that the benefits of providing cue polarity through strategy selection will be greatest in tasks that can be accurately solved by rule-based strategies such as linear judgment tasks and thus people can benefit from using the more accurate strategy in such situations. The effects of cue polarity information on strategy selection suggest that providing cue polarity information could sometimes also lead to negative consequences. When a task cannot be solved by a rule-based strategy, as for example in a task with a quadratic relation between cues and criterion, a bias toward cue abstraction could be detrimental to performance (Olsson et al., 2006).

In the categorization task, strategy selection did not have an impact on performance, even though in principle a cue abstraction strategy should outperform an exemplar strategy, because the former matches the (linear) task structure. One possible explanation is that performance differences in the categorization task were masked by the binary nature of the criterion that is less sensitive than the fine-grained criterion in the judgment task. However, analyses using an equally coarse performance measure for the multiple-cue judgment task and the categorization tasks rendered a similar pattern of results. Alternatively, it could be that in categorization cue abstraction users do not learn to execute the cue abstraction strategy well enough to allow performance differences between strategies to manifest themselves. This explanation is also in line with the finding that the explicit knowledge about cue importance for cue abstraction users tended to be higher in the judgment than in the categorization task.

We also found that providing cue polarity information led to better explicit knowledge of relative cue importance (study 2). One novel aspect of our results is the finding that although cue abstraction users had better explicit knowledge about cue importance than exemplar users, explicit knowledge of cue importance was associated with improved performance independent of the task and the strategy used. This finding is particularly noteworthy because it challenges the idea that explicit knowledge is irrelevant when similarity-based processes are used that some have argued to be of an implicit nature (e.g., Ashby et al., 1998). There are at least two different interpretations of this finding. First, one could interpret these results as suggesting that similarity-based processes can benefit from explicit knowledge of relative cue importance. For instance, explicit knowledge about cue importance could increase performance by guiding attention given to each cue when using a similarity-based process. However, and alternatively, one could interpret the benefits of explicit knowledge in categorization as suggesting that participants did not rely on a pure similarity-based strategy but instead relied on integration of rule-based and similarity-based processes (Erikson and Kruschke, 1998; von Helversen et al., in press). According to such an interpretation, the performance benefits provided by explicit knowledge would result from any benefits obtained through improved cue abstraction. One should note that our results on explicit knowledge are of correlational nature. Thus, we cannot say if explicit knowledge caused better performance or was a by-product of a more efficient process. Clearly, future studies are needed that distinguish between these possibilities and investigate the link between explicit task knowledge and similarity-based processes in inference tasks.

5. Conclusion

Our results suggest that prior knowledge about cue polarity can be a powerful tool to generate performance benefits in inference. In both a judgment and a categorization task, participants learnt faster and performed better in a generalization test when cue polarity information was provided. Although cue polarity information increased reliance on rule-based strategies and knowledge about cue importance, the relative importance of these two mechanisms for performance depended on the task. While increased reliance a rule-based strategy only improved performance in the judgment task, knowledge about cue importance increased performance independently of the task and the strategy used. Our results suggest that instructing human judges through providing cue polarity information can have broader impact on task representations by improving the knowledge of cue importance that has the potential to improve both categorization and multiple-cue judgment.

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Tables

Table 1. Structure of the Task

Item	Cue 1	Cue 2	Cue 3	Cue 4	$Crit_{con}$	CAM_{con}	EBM_{con}	$Crit_{bin}$	CAM_{bin}	EBM_{bin}	Training /Test
1	0	0	0	0	10	10.0	12.4	0	0.0	0.0	Test
2	0	0	0	1	11	11.0	11.0	0	0.0	0.0	Training
3	0	0	1	0	12	12.0	12.0	0	0.0	0.1	Training
4	0	0	1	1	13	13.0	13.0	0	0.0	0.1	Training
5	0	1	0	0	13	13.0	13.0	0	0.0	0.0	Training
6	0	1	0	1	14	14.0	14.0	0	0.0	0.1	Training
7	0	1	1	0	15	15.0	13.8	.5	1.0	0.6	Test
8	0	1	1	1	16	16.0	16.0	1	1.0	0.8	Training
9	1	0	0	0	14	14.0	14.0	0	0.0	0.1	Training
10	1	0	0	1	15	15.0	14.1	.5	0.0	0.2	Test
11	1	0	1	0	16	16.0	16.0	1	1.0	0.9	Training
12	1	0	1	1	17	17.0	17.0	1	1.0	0.9	Training
13	1	1	0	0	17	17.0	13.5	1	1.0	0.2	Test
14	1	1	0	1	18	18.0	17.1	1	1.0	0.4	Test
15	1	1	1	0	19	19.0	18.2	1	1.0	0.9	Test
16	1	1	1	1	20	20.0	20.0	1	1.0	1.0	Training

Note. Training items appeared during training and test. The test items only appeared during test. $Crit_{con}$ = criterion in the judgment task; $Crit_{bin}$ = criterion in the categorization task; CAM_{con} and CAM_{bin}= prediction cue abstraction model in the judgment and the categorization task respectively; EBM_{con} and EBM_{bin}= prediction of the exemplar model in the judgment and the categorization task respectively. Model predictions were obtained by fitting the models' free parameters to the criterion values of the training items and predicting the responses to the test items based on the estimated parameters.

Table 2. Training and test performance by task and information in study 1

		Judgment		Categorization	
		Without information	With information	Without information	With information
N		25	25	25	19
Nr. blocks training	*M*	11.04	8.24	9.08	8.16
	SD	3.30	1.20	2.25	0.50
Performance: Last block of training	*M*	1.29	0.65	0.28	0.22
	SD	0.75	0.57	0.19	0.20
Performance: Test old	*M*	1.17	0.64	0.25	0.16
	SD	0.75	0.52	0.19	0.21
Performance: Test new	*M*	1.81	0.85	0.46	0.46
	SD	0.82	0.72	0.17	0.12

Note. Performance was measured as the root mean square deviation between participants' responses and the criterion.

Table 3. Number of participants classified as using a cue abstraction or exemplar model in study 1

	Without information		With information	
Task	EBM	CAM	EBM	CAM
Judgment	7	13	2	20
Categorization	13	5	2	17
Total	20	18	4	37

Note: CAM = cue abstraction model; EBM = exemplar model.

Table 4. Means and SD of performance (RMSD) by task and information in study 2

		Judgment		Categorization	
		Without information	With information	Without information	With information
N		38	37	41	39
Nr. blocks training	*M*	17.37	9.54	12.80	7.10
	SD	4.85	5.88	5.86	5.41
Performance: Last block of training	*M*	1.65	0.92	0.13	0.02
	SD	0.96	0.94	0.23	0.09
Performance: Test old	*M*	1.44	0.66	0.21	0.15
	SD	0.74	0.69	0.18	0.13
Performance: Test new	*M*	2.24	1.01	0.53	0.43
	SD	0.96	0.86	0.14	0.13
Cue importance knowledge	*M*	45.63	28.05	59.02	45.64
	SD	25.30	29.18	24.10	19.16

Table 5. Number of participants classified as using a cue abstraction or exemplar model in study 2

	Without information		With information	
Task	EBM	CAM	EBM	CAM
Judgment	23	11	5	31
Categorization	25	12	9	28
Total	48	23	14	59

Note: CAM = cue abstraction model; EBM = exemplar model.

Table 6: Hierarchical regression analysis on accuracy in the test phase

Predictor	beta	*t*(df)	*p*-value
	Judgment		
Model 1:			
Cue polarity information	-0.56	5.62 (68)	.001
Model 2:			
Cue polarity information	-0.17	2.19 (66)	.03
Strategy classification	-0.49	5.69 (66)	.001
Cue importance knowledge	0.39	5.25 (66)	.001
	Categorization		
Model 1:			
Cue polarity information	-0.30	2.70 (72)	.009
Model 2:			
Cue polarity information	-0.21	1.67 (70)	.10
Strategy classification	-0.03	0.27 (70)	.79
Cue importance knowledge	.48	3.30 (70)	.002

Note: Judgment R^2 = .71; Categorization R^2 = .18

Figures

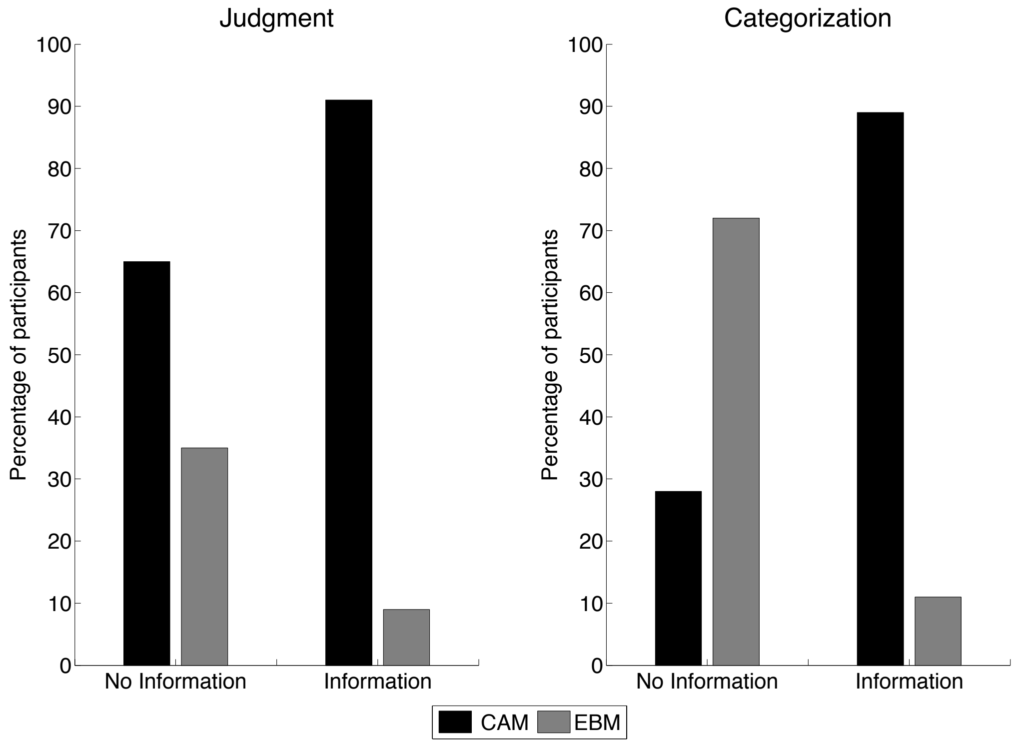

Figure 1. Percent of participants in study 1 classified as using the cue abstraction model and the exemplar model in the judgment task (left panel) and in the categorization task (right panel). CAM = cue abstraction model; EBM = exemplar model.

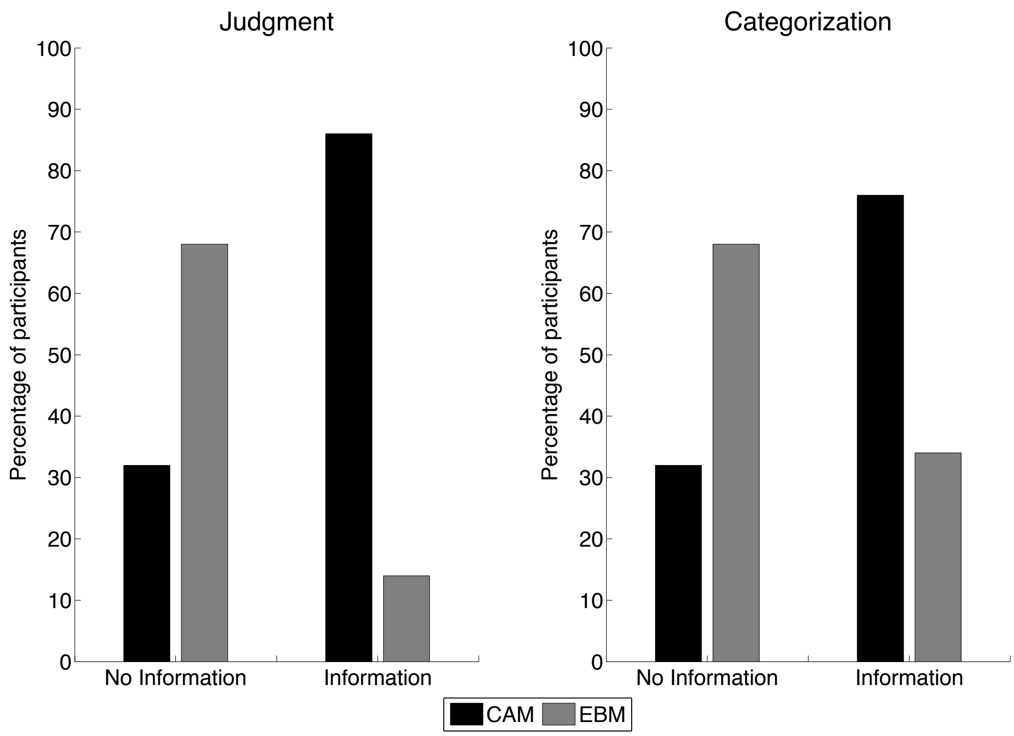

Figure 2. Percent of participants in study 2 classified as using the cue abstraction model and the exemplar model in the judgment task (left panel) and in the categorization task (right panel). CAM = cue abstraction model; EBM = exemplar model.